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Exploring Longitudinal Measurement Invariance and the Continuum Hypothesis in the Swedish Version of the Behavioral Regulation in Sport Questionnaire (BRSQ): An Exploratory Structural Equation Modeling Approach

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Abstract

Objectives: The aims of the present study were to: (a) examine longitudinal measurement invariance in the Swedish version of the Behavioral Regulations in Sport Questionnaire (BRSQ) and (b) examine the continuum hypothesis of motivation as postulated within self-determination theory.

Design: Two-wave survey.

Method: Young competitive athletes (*N* = 354) responded to the BRSQ early in the season (November) and at the end of the athletic season (April). Data were analyzed using exploratory structural equation modeling (ESEM) and bifactor ESEM.

Results: We found support for strict longitudinal measurement invariance in the BRSQ. Latent mean comparisons showed an increase in external regulation and amotivation across the season. The latent factor correlations indicated some deviations from a simplex pattern related to amotivation, external regulation, and introjected regulation. In the bifactor model, intrinsic motivation items had negative factor loadings on the global factor, identified regulation items had factor loadings approaching zero, and introjected and external regulation and amotivation items all had moderate to strong positive factor loadings.

Conclusion: The present study adds longitudinal measurement invariance to the psychometric evidence of the BRSQ. Research on why the latent means of the behavioral regulations changed over the athletic season is warranted. The continuum hypothesis was partially supported. Latent factor correlations and factor loadings on the global factor in the bifactor ESEM highlighted that the discriminant validity of the controlled regulations and amotivation needs further investigation.

Keywords: latent mean changes; motivation continuum; self-determination theory; temporal stability

Motivation is a prominent area of research in sport and exercise psychology (Lindahl, Stenling, Lindwall, & Colliander, 2015) and one of the dominant theories in contemporary motivation research is self-determination theory (SDT; Ryan & Deci, 2017). Within the confines of SDT, motivation is conceptualized along a continuum specifying types of motivational regulations that varies according to the extent that they are self-determined. These motivational regulations ranges from autonomous/self-determined types (intrinsic motivation, integrated regulation, and identified regulation), controlled types (introjected regulation and external regulation) to amotivation and have shown different associations to various outcomes among athletes (e.g., Hagger & Chatzisarantis, 2007; Ntoumanis, 2012). Autonomous types of motivation have generally been associated with adaptive outcomes, such as mental and physical health (e.g., Li, Wang, Pyun, & Kee, 2013; Ng et al., 2012) and better performance (Cerasoli, Nicklin, & Ford, 2014), whereas the controlled types of motivation and amotivation often have been related to maladaptive outcomes, such as ill-being (Ng et al., 2012; Wang et al., 2013) and worse performance (Gillet, Vallerand, & Rosnet, 2009).

There are several SDT-based measures for athletes' motivational regulations (see Clancy, Herring, & Campbell, 2017 for a recent review) and one of the more recently developed, and well cited, is the Behavioral Regulation in Sports Questionnaire (BRSQ; Lonsdale, Hodge, & Rose, 2008) tapping the various types of motivational regulations towards athletes' sports participation. Although the psychometric properties of the BRSQ have been scrutinized psychometrically by several scholars (e.g., Lonsdale et al., 2008; Viladrich et al., 2013) and have been translated to several languages (e.g., Dutch: Assor, Vansteenkiste, & Kaplan, 2009; Chinese: Chan, Hagger, & Spray, 2011; Greek: Mouratidis, Lens, & Vansteenkiste, 2010), several psychometric issues still remain to be explored. In the present study, we continued the psychometric evaluation of the BRSQ and examined longitudinal measurement invariance of the Swedish version of the BRSQ. Longitudinal measurement invariance has not been examined in previous research with any version of the BRSQ.

Scholars have in recent years have utilized advanced statistical methods (e.g., bifactor modeling and exploratory structural equation modeling) to examine the continuum hypothesis within SDT (Chemolli & Gagné, 2014; Guay, Morin, Litalien, Valois, & Vallerand, 2015; Howard, Gagné, Morin, & Forest, 2016; Litalien, Guay, & Morin, 2015; Litalien et al., 2017). According to the continuum hypothesis, the motivational regulations should form a continuum from highly autonomous types on the one end of the continuum to controlled types and amotivation on the other end (Ryan & Deci, 2017). As such, this hypothesis is also applicable to the BRSQ (Lonsdale et al., 2008). Given the recent interest in the continuum hypothesis in other domains (e.g., education, work, physical activity; Chemolli & Gagné, 2014; Guay et al., 2015; Gunnell & Gaudreau, 2015; Howard et al., 2016; Litalien et al., 2017), it is essential to test SDT's continuum hypothesis also in measures developed for sports settings, which we aim to do in the present study.

Motivation According to Self-Determination Theory

People's choice to participate, put in effort, and sustain their engagement in an activity can be classified along a self-determination continuum representing different levels of internalization of the regulation of a behavior (Ryan & Deci, 2000). Intrinsic motivation represents peoples natural tendencies towards development and do not result from internalization. It is defined as engagement driven by the inherent joy in the activity itself characterized by volition and a sense of freedom without the necessity of separable consequences. At the other end of the continuum lies amotivation, defined as an absence of motivation towards the activity. Amotivated persons do not value the activity or the outcomes associated with it. Between these two extremes are different types of extrinsic motivation.

External regulation is the least self-determined type of those extrinsic motivational regulations and is defined as engagement in an activity for instrumental reasons where no internalization has occurred. Introjected regulation is when the reasons for engaging in the activity has been partially internalized but not accepted as one's own and is characterized by internal pressures to avoid shame and guilt or to enhance ego and self-worth. Identified regulation is largely internalized and is present when the person values the outcome of the activity as personally important. Integrated regulation—the most self-determined type of extrinsic regulation—is present when the person views the activity to be in line with his or her personal values and sense of self.

The Continuum Hypothesis

Within SDT, motivation is conceptualized as different regulations ordered along a continuum elucidating the degree of self-determination (Ryan & Deci, 2017). The qualitatively different types of motivation are also suggested to differ quantitatively along the single continuum of self-determination (Howard et al., 2016). Researchers have typically used factor correlations to examine the continuum hypothesis and argued that adjacent types of motivational regulations should correlate more strongly compared to more distal types (Li, 1999; Li & Harmer, 1996; Ryan & Connell, 1989). Although past research has provided some support for the continuum hypothesis, recent research has cast doubts on this expectation, particularly when more advanced statistical techniques are used (Chemolli & Gagné. 2014; Guay et al., 2015). For example, Chemolli and Gagné (2014) argued that if the motivational regulations align along a continuum, a confirmatory factor analysis (CFA) should support a one-factor model with negative factor loadings on the least self-determined types and positive factor loading on the more self-determined types. Using Rasch analysis no support was found for a unidimensional model (i.e., items loading onto a single motivation factor); the results clearly supported a multidimensional model (i.e., items loading onto distinct subdimensions of motivation; cf. Gagné et al., 2015; Mallet, Kawabata, Newcombe, Otero-Forero, & Jackson, 2007).

Others have taken a slightly different approach and used exploratory structural equation modeling (ESEM; Asparouhov & Muthén, 2009; Marsh, Morin, Parker, & Kaur, 2014) to evaluate the continuum hypothesis. Using ESEM, researchers have for example examined the factor correlation pattern of academic motivation (Guay et al., 2015 in the Academic Motivation Scale), motivation for PhD studies (Litalien et al., 2015), and sport motivation (Viladrich et al., 2013 in the BRSQ). Given that ESEM provide more accurate factor correlations (Marsh et al., 2014), ESEM should result in a clearer simplex pattern compared to the independent clusters model (ICM) CFA. Viladrich et al. (2013) found support for a simplex pattern of sport motivation in the BRSQ, whereas deviations from a simplex pattern were observed in Litalien et al. (2015) and Guay et al. (2015).

Researchers have also operationalized motivation as consisting of a general factor representing motivation quantity and specific factors representing the different motivational regulations (i.e., motivation quality) in physical activity settings (Gunnell & Gaudreau, 2015). By specifying a bifactor ESEM, it was found that all types of motivation, including amotivation, were positively associated with the general motivation factor. The general motivation factor, identified motivation, and intrinsic motivation were also positively associated with physical activity and the general motivation factor longitudinally predicted goal progress. These findings suggest that all types of motivational regulations, including amotivation, contribute to peoples' pool of motivational resources (Gunnell & Gaudreau, 2015). Furthermore, when examining the cross-loadings in the bifactor ESEM some support for the continuum hypothesis was shown by the stronger cross-loadings in the expected direction on more adjacent non-target factors. Howard et al. (2016), however, found a slightly different pattern in work settings where the factor loadings on the general motivation factor supported the continuum hypothesis indicated by a shift in magnitude and sign from the autonomous types of motivation to the controlled types of motivation and amotivation. Similarly, Litalien and colleagues (2017) provided evidence of a continuum structure of academic motivation in two student samples and the results largely mirrored those presented by Howard et al. (2016) in work settings. With a simultaneous assessment of a global motivation factor and specific factors representing the behavioral regulations the factor loadings on the general factor shifted in magnitude along the continuum from the autonomous types of motivation to the controlled types of motivation and amotivation.

The Present Study

In the present study we build on and extend previous research by Chemolli and Gagné (2014), Guay et al. (2015), Gunnell and Gaudreau (2015), Howard et al. (2016), and Litalien et al. (2017) and apply longitudinal ESEM and bifactor ESEM to the BRSQ (Lonsdale et al., 2008). One important psychometric property of a measurement instrument is longitudinal stability or invariance (Meredith, 1993; Widaman, Ferrer, & Conger, 2010). As in multigroup analyses investigating whether people from different populations or subgroups interpret the items and latent constructs in a similar way, the same questions are addressed within groups over time by examining longitudinal measurement invariance (Vandenberg & Lance, 2000). With regard to the BRSQ, scholars have examined measurement invariance across age, culture, and sex in cross-sectional studies (Hancox, Quested, Viladrich, & Duda, 2015; Lonsdale et al., 2008; Viladrich et al., 2013), however, longitudinal stability of the BRSQ is still unexplored. A key assumption when conducting longitudinal research and investigating change or interrelationships across time is that we are measuring the same thing in the same metric at each time point, which is referred to as factorial invariance across time or longitudinal measurement invariance (Widaman et al., 2010). If factorial invariance constraints are satisfied, it can be assumed that the same latent construct is assessed at each time points, thus ensuring more accurate conclusions about latent or observed mean changes. Although the BRSQ have been used to assess changes in motivation following an intervention among athletes (Langan, Blake, Toner, & Lonsdale, 2015), factorial invariance across time in the BRSQ is still unexplored.

In this study we examined four types of measurement invariance: configural, metric, scalar, and strict invariance (Horn & McArdle, 1992; Little, 2013; Lance & Vandenberg, 2000; Meredith, 1993). With configural invariance we examine whether the same pattern of fixed and free factor loadings is specified at each time point. Configural invariance needs to be established before any additional invariance test can be deemed meaningful. A secondary step is to examine metric invariance, referring to invariant factor loadings across time, and indicates that the same meaning is ascribed to the latent construct across time. Scalar invariance refers to equality constraints on the intercepts and implies that the item scores have the same scaling across time (i.e., item scores share a common zero point). Strict invariance implies that the reliability of the items is invariant as indicated by the constraints of the items' uniqueness across time. Metric invariance is necessary to compare structural relations across time, scalar invariance is necessary to compare latent mean scores across time, whereas strict invariance is necessary to compare manifest scores over time (Little, 2013; Marsh et al., 2013).

A natural extension of measurement invariance testing as described in the previous paragraph is to examine changes in latent means across time. The data were collected early in the season (T1) and late in the season (T2) making it suitable to examine seasonal changes in the behavioral regulations. Studies on latent mean changes in behavioral regulations are scarce in the sport psychology literature. Minor decreases in intrinsic motivation across the athletic season have been reported among Division 1 collegiate athletes (Amorose & Horn, 2001). Lonsdale and Hodge (2011) observed increases in amotivation, external regulation, and introjected regulation, and decreases in identified regulation and intrinsic motivation across a four-month period in a varied sample of athletes in New Zealand. These studies did not, however, assess latent mean changes in longitudinally invariant models, and were therefore at risk of not measuring the same latent construct in the same metric at the each time point (cf. Widaman et al., 2010). Findings from the educational domain suggest that academic motivation decreases across adolescence and research examining latent mean changes show that intrinsic motivation and all of the extrinsic regulations decreases from age 11 to age 16 (Gnamb & Hanfsting, 2016; Otis et al., 2005). Based on these previous findings we expect that the behavioral regulations towards sport might change across an athletic season and estimate latent mean changes in a longitudinally invariant measurement model to assess true changes in the latent constructs over time in an athletic sample. We did not have specific hypothesis about the behavioral regulations because of the unavailability of previous research on latent mean changes over time in athletes.

Building on previous research we also examined the continuum hypothesis in the present study (Chemolli & Gagné, 2014; Guay et al., 2015; Gunnell & Gaudreau, 2015; Howard et al., 2016; Litalien et al., 2017). We used ESEM models to examine the simplex pattern of factor correlations where stronger factor correlations between more adjacent factors would support the notion of a continuum structure (Ryan & Connell, 1989). We also specified a bifactor ESEM model (Morin, Arens, & Marsh, 2016) to simultaneously conceptualize motivation as unidimensional (i.e., motivation quantity) and multidimensional (i.e., motivation quality; cf. Gunnell & Gaudreau, 2015; Howard et al., 2016; Litalien et al., 2017). By accounting for two types of construct-relevant psychometric multidimensionality as specified by the global and the specific factors, both motivation quantity and quality can be assessed in the same model. Because of the inherent orthogonality in bifactor models, the global factor will capture athletes' overall quantity of motivation whereas the specific factors will reflect the motivation quality of athletes' motivation profiles (Howard et al., 2016). A shift in magnitude and sign of the factor loadings on the global factor along the SDT continuum would support the continuum hypothesis (Chemolli & Gagné, 2014). To summarize, the specific aims of the present study were to: (a) examine longitudinal measurement invariance in the BRSQ and (b) examine SDT's continuum hypothesis of motivation in a sport context.

Methods

Participants and Procedure

A convenience sample of 354 (48% females) young competitive athletes (skiers [alpine, biathlon, cross-country] = 46%; floorball players = 54%) ranging from 15 to 21 years of age (*M* = 17.2; *SD* = 1.16) was included in the present study. The competitive level ranged from regional to international level. The athletes had on average been competing in their sport for 9 years (*SD* = 2.8).

The head coach of each team was contacted and informed about the purpose of the study and asked for permission to approach the athletes with an invitation to participate in the study. When permission was granted, an information meeting was scheduled and the athletes were invited to participate. The first questionnaire was administered approximately two months into the competitive season (November), and the second at the end of the competitive season (April). Ethical approval was obtained from the Regional Ethical Review Board at the first author's university prior to data collection.

Measures

Behavioral regulations. A Swedish version of the Behavioral Regulation in Sport Questionnaire (BRSQ, Lonsdale, Hodge, & Rose, 2008) was used to assess athletes' behavioral regulations toward their sports participation. Participants were asked to indicate how well the items corresponded to their reasons for participating in sports, responding on a seven-point Likert scale from 1 (*not true at all*) to 7 (*very true*). The item stem was "I participate in my sport…". The version of BRSQ used in this study included five four-item subscales designed to measure amotivation (e.g., "but I question why I continue"), external regulation (e.g., "in order to satisfy people who want me to play"), introjected regulation (e.g., "because I would feel like a failure if I quit"), identified regulation (e.g., "because I value the benefits of my sport"), and intrinsic motivation (e.g., "because I enjoy it"). We used a five-factor version of the BRSQ because of the known problems with the integrated regulation subscale, such as lack of discriminant validity and that a questionnaire format may not be well suited to assess integrated regulation (Lonsdale et al., 2008; see also Viladrich et al., 2013), and the assertion that this type of regulation is not prevalent until adulthood (Vallerand, 1997).

The BRSQ was translated into Swedish using a forward-translation approach (Hambleton, Merenda, & Spielberger, 2004). The English version was translated into Swedish by the first author and then the translation was reviewed by three bilingual members of the research group with expertise in sport psychology, motivation, and psychometrics. Disagreements regarding the translation were discussed until consensus was reached. The translated version was also subjected to pilot testing with a small group of sport psychology students (N = 3) who provided comments on Swedish version that were taken into consideration before the final version was determined. To further examine the psychometric properties of the BRSQ we performed a comparison between the Swedish sample and a New Zealand-based sample (an age-matched sample collapsed across Study 1, 2, and 3 in Lonsdale et al., 2008) responding to the original English version of the BRSQ. The results showed partial scalar invariance (i.e., three intercepts were freely estimated) across the two samples. Details of the measurement invariance testing are outlined in Supplementary Materials Appendix 2.0.

Statistical Analysis

We used Mplus version 8.0 (Muthén & Muthén, 1998-2017) and the robust full information maximum likelihood estimator (MLR) to analyze the data. All 354 athletes responded to the questionnaire at both time points and there were less than 2% missing data at the item level across the two time points, which was accounted for by the full information MLR (Enders, 2010). Items were treated as continuous, which is reasonable with seven response categories (Rhemtulla, Brosseau-Liard, & Savalei, 2012).

All analyses were conducted within an ESEM framework (Asparouhov & Muthén, 2009; Marsh, Morin, Parker, & Kaur, 2014; Morin, Arens, & Marsh, 2016). Recent research indicates that the specification of zero cross-loadings on non-target latent factors in the ICM-CFA often renders poor model fit and attenuated factor correlations (Asparouhov & Muthén, 2009; Marsh et al., 2014). Morin et al. (2016) refers to this as the fallible nature of indicators, meaning that there is most often some systematic association between indicators and non-target latent factors. Most items are imperfect to some degree and have some systematic association with other constructs (Morin et al., 2016), hence, cross-loadings can typically be justified based on substantive theory or item content in multidimensional measures (Asparouhov & Muthén, 2009). That factor correlations are more accurately estimated in ESEM but likely to be positively biased in ICM-CFA have consistently been shown in both simulated data (e.g., Asparouhov & Muthén, 2009) and empirical data (Marsh, Lüdtke, Nagengast, & Morin, 2013). We used target rotation (Browne, 2001; Asparouhov & Muthén, 2009) in the ESEM models that allows for the specification of factor loadings on target and non-target latent factor in a confirmatory manner. All cross-loadings were specified to be close to zero but not exactly zero, whereas the main factor loadings were freely estimated (Morin et al., 2016).

Although most longitudinal measurement invariance studies have been performed within a CFA framework, the same logic applies when testing longitudinal invariance within the ESEM framework (cf. Marsh et al., 2010). We specified increasingly constrained models to examine temporal invariance in the BRSQ following the Meredith (1993) tradition. First, a configural model is estimated, which evaluates the similarity in the overall pattern of parameters across time. Note, however, that no equality constraints are imposed in the configural model, it provides a test of the a priori model at each time point and how it fits the data against which subsequent models with constraints can be compared. Second, a metric invariance model is estimated, in which the factor loadings are constrained to be invariant across time. Third, a scalar invariance model is estimated where the item intercepts and factor loadings are constrained to be invariant across time. By establishing scalar invariance researchers can reasonably interpret changes in the latent factor means as changes in the latent constructs (Marsh et al., 2010). Fourth, we assessed strict measurement invariance by constraining the items' uniquenesses to equality across time. Strict measurement invariance is an important prerequisite for testing mean differences in manifest scale scores (or factor scores) because differences in reliability could distort mean differences on the observed scores (Marsh et al., 2013). Finally, we estimated latent mean changes in the behavioral regulations across time. Composite reliability was computed according to McDonald's (1970) $\omega = (\Sigma|\lambda i|)^2/([\Sigma|\lambda i|^2] + \Sigma\delta ii)$ using the standardized parameters from the most invariant longitudinal model where λi are the factor loadings and δii are the error variances.

The bifactor ESEM was specified with a general motivation factor alongside five specific factors representing the different behavioral regulations according to the recently proposed bifactor ESEM framework by Morin et al. (2016). The specific factors in bifactor models explains item variance unaccounted for by the general factor and the general factor explains variance shared across all items. To ensure interpretability and adhering to bifactor assumptions the specific and general factors were specified as orthogonal (Chen, West, & Sousa, 2006; Reise, 2012). The ESEM and bifactor ESEM are graphically depicted in Figure 1.

Model fit was evaluated with conventional fit indices such as the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the standardized root mean residual (SRMR), and the root mean square error of approximation (RMSEA). CFI and TLI values around 0.90 and SRMR and RMSEA values around 0.08 indicated acceptable model fit (Marsh, 2007). The nested longitudinal invariance models were evaluated using Chen's (2007) recommendations that change in CFI (ΔCFI) of less than 0.01 and change in RMSEA (ΔRMSEA) of less than .015 or a change in SRMR (ΔSRMR) of less than 0.030 would support metric invariance. For scalar and strict invariance a change in CFI (ΔCFI) of less than 0.01 and change in RMSEA (ΔRMSEA) of less than .015 or a change in SRMR (ΔSRMR) of less than 0.010 would indicate invariance across time. It is important to remember that these are all rough guidelines, not "golden rules" (Marsh, Hau, & Wen, 2004), developed within a CFA framework; it is still unclear how relevant they are for ESEM applications (Marsh et al., 2009). As noted by Marsh et al. (2010) "Ultimately, however, an evaluation of goodness of fit must be based upon a subjective integration of many sources of information, including fit indices, a detailed evaluation of parameter estimates in relation to a priori hypotheses, previous research, and common sense" (p. 477). Mplus syntax for all analyses can be found in Appendix 1.1 to 1.6 in the Supplemental Materials.

Results

Descriptive Statistics and Preliminary Analyses

Item statistics are displayed in Table 1, showing means, standard deviations, skewness, and kurtosis of each item at T1 and T2. Some items, particularly those with very high or low mean values, displayed non-normal response patterns as indicated by the skewness and kurtosis values. The participants reported high levels on the intrinsic motivation items ($M > 6.0$), moderate levels on the identified regulation items ($M \approx 4.5$ to 5.6), and low levels on the introjected regulation, external regulation, and amotivation items ($M < 2.1$).

As recommended by Marsh and colleagues (e.g., Marsh et al., 2009, 2010), we compared the ICM-CFA model with the ESEM model at T1 and T2 (see Table 2). The ESEM models displayed a better fit to the data at both time points (e.g., > CFI, < SRMR) but the difference in model fit was more pronounced at T2. As expected the magnitude of the correlations between the latent factors were larger in the ICM-CFA models (*r* range at T1 -0.72 to 0.90; *r* range at T2 -0.71 to 0.88) compared to the ESEM models (*r* range at T1 -0.65 to 0.64; *r* range at T2 -0.62 to 0.67). Latent factor correlations of this magnitude in the ICM-CFA call into question the instruments ability to discriminate between the factors. Taken together, these findings suggest that the ESEM provide a better fit to the data and we therefore relied on ESEM in the remaining analyses.

Longitudinal Measurement Invariance and Latent Mean Changes

Model fit of the increasingly constraint models compared in the longitudinal invariance testing are displayed in Table 2. Model fit of the configural model was acceptable, making it adequate to examine metric invariance as a second step. The model fit of the metric invariance model, with the factor loadings constraint to equality over time, did not display a decrease in any of the model fit indices that would suggest non-invariance (ΔCFI = -0.06; ΔRMSEA = 0.00; ΔSRMR = 0.012). In the third step, we estimated the scalar invariance model where the intercepts were constraint to equality over time. The change in CFI, RMSEA, and SRMR (ΔCFI = -0.04; ΔRMSEA = 0.00; ΔSRMR = 0.03) indicated that the model was fully invariant over time. Finally, the strict invariance model also indicated full invariance of the items' uniquenesses over time (ΔCFI = -0.04; ΔRMSEA = -0.01; ΔSRMR = 0.06). These results suggest full longitudinal measurement invariance in the BRSQ over a five-month period. The standardized factor loadings of the strict invariance model are displayed in Table 3 and shows well defined target factors and relatively weak cross-loadings (< 0.30). The ESEM-based composite reliability coefficients (ω) ranged from 0.72 to 0.83 (M_{ω} = 0.77). The latent mean comparisons showed that the changes in intrinsic motivation (-0.108, p = 0.081), identified regulation (0.032, p = 0.617), and introjected regulation (0.140, p = 0.097) were not statistically significant, whereas changes in external regulation (0.230, p = 0.007) and amotivation (0.194, p = 0.019) were statistically significant and increased across the season.

The Continuum Hypothesis

The latent factor correlations generally supported a simplex pattern with stronger factor correlations between more adjacent factors and weaker factor correlations between more distal factors both within and across time points (Table 4). There were, however, minor deviations from a simplex pattern. The association between amotivation at T1 and introjected regulation (T1 r = 0.63, T2 r = 0.38) was slightly larger than the association between amotivation at T1 and external regulation (T1 r = 0.58, T2 r = 0.29). Amotivation at T2 also showed a slightly stronger association with introjected (r = 0.43) than external regulation (r = 0.41) at T1.

Inspection of the pattern in the bifactor ESEM at T1 showed a shift in the factor loadings sign and magnitude on the global factor when moving from intrinsic motivation to amotivation (Table 5). Whereas the intrinsic motivation items show negative factor loadings on the global factor (λ ranging from -0.352 to -0.618), identified regulation items shows factor loadings approaching zero (λ ranging from -0.005 to 0.180), and introjected and external regulation and amotivation items all had positive and moderate to strong factor loadings (λ ranging from 0.514 to 0.778) on the global factor. The factor loading pattern on the global factor did not indicate a continuous shift along the continuum, but rather a shift between intrinsic motivation and identified regulation, and also between identified regulation and introjected regulation. The factor loading pattern at T2 was similar to the pattern at T1, but we had to remove one identified regulation item ("*because the benefits of sport are important to me*") from the analysis of the T2 data due to a negative error variance estimate (see Table 5). Taken together, these results show somewhat mixed support for the continuum hypothesis but seem to indicate qualitative differences between intrinsic motivation, identified regulations, and the controlled regulations and amotivation.

Discussion

The aims of the present study were (a) to examine longitudinal measurement invariance in the BRSQ and (b) to examine SDT's continuum hypothesis of motivation in a sport context. To summarize, we found support for strict longitudinal measurement invariance in the BRSQ in a sample of young competitive athletes and observed statistically significant latent mean changes in external regulation and amotivation across the season. In addition, the results showed some support for a sport motivation continuum.

Longitudinal Measurement Invariance of the BRSQ

Previous research has demonstrated measurement invariance of the BRSQ across different groups, such as age, sex, and cultural (e.g., Hancox et al., 2015; Lonsdale et al., 2008; Viladrich et al., 2013). This is the first study demonstrating longitudinal measurement invariance of any version of the BRSQ further adding to the psychometric evidence of the instrument in sport settings. According to the model fit criteria both metric, scalar, and strict invariance were supported, indicating that the athletes ascribe the same meaning to the latent constructs, that the item scores have the same scaling (i.e., item scores share a common zero point), and that the reliability of the items are equal across time. Establishing measurement invariance over time is a crucial step in a psychometric evaluation because it implies that the same latent construct is measured in the same metric across time (Widaman et al., 2010). If measurement invariance across time is not achieved, observed changes may be caused by a recalibration of the metric or by a redefinition or reconceptualization of the latent construct, referred to as beta and gamma change (Golembiewski, Billingsley, & Yeager, 1976; Millsap & Hartog, 1988), respectively. In other words, when longitudinal measurement invariance constraints are not satisfied, researchers faces the risk of comparing apples and oranges across time. Satisfying measurement invariance constraints allows for comparisons of means (latent and observed) across time because if changes are observed they can be interpreted as “true” changes in the underlying latent construct, not as changes in the interpretation of the items or latent construct (Golembiewski et al., 1976; Marsh et al., 2010; Millsap & Hartog, 1988). As such, it is reassuring that the accumulating evidence of the psychometric properties of the BRSQ now also includes a solid base for conducting longitudinal research and examining mean comparisons of the regulations across time. However, we encourage researchers collecting longitudinal data to assess measurement invariance across time in their samples whenever possible.

Latent Mean Changes in the Behavioral Regulations

The latent mean comparisons indicated an increase in external regulation and amotivation towards the end of the season. This may reflect that the athletes perceive an increased pressure (particularly external) towards the end of the season when competitions deemed more important are held and their performances over the season are being summarized. The increase in amotivation may also reflect a devaluation of the sport engagement or potentially a decrease in perceived competence as the season progresses. Exploring changes in behavioral regulations as a consequence of performance outcomes, activity participation, or across critical or naturally occurring events would aid our understanding of the complex interactions between behavioral regulations and activity participation. For example, in a recent two-wave study children’s school- and leisure-time, physical activity prospectively predicted autonomous motivation towards physical education, but not vice versa (Taylor, 2017). These results suggest that common outcomes in SDT research, such as physical activity or performance in competitive sports (see e.g., Blanchard, Mask, Vallerand, de la Sablonnière, & Provencher, 2007), may influence if and how people internalize the reasons for partaking in these activities. Researching if and how engaging in different activities influences behavioral regulations and internalization is an interesting area for future research.

The Continuum Hypothesis

We also examined the continuum hypothesis proposed within SDT by examining the pattern of latent factor correlations and by simultaneously examining motivation quality and motivation quantity in a bifactor ESEM model. The general pattern of correlations between the latent factors suggested a simplex pattern with stronger correlations between more adjacent factors and weaker correlations between more distal factors. However, we did observe some deviations from the simplex pattern related to the associations between amotivation, external regulation, and introjected regulation. Similar deviations from a simplex pattern in the BRSQ have been reported in previous research (see Hancox et al., 2015; Lonsdale et al., 2008). We also observed high latent factor correlations, particularly between external and introjected regulation but also between external regulation and amotivation, despite using ESEM that is known to reduce attenuated correlations in measurement models (Marsh et al., 2014). These observations also mirror previous findings showing that the discriminant validity of the BRSQ sub-dimensions, particularly of the controlled types of motivation and amotivation, needs further investigation (e.g., Hancox et al., 2015; Lonsdale et al., 2008).

The fact that the factor loadings onto the global factor in the bifactor ESEM model suggested two shifts along the continuum–between intrinsic motivation and identified regulation and between identified regulation and introjected regulation–is partly in line with the continuum of relative autonomy as outlined within SDT (Ryan & Deci, 2017). When comparing the results from the present study with similar studies in other domains, there are some noticeable differences. Results from two recently published bifactor ESEM studies in the educational (Litalien et al., 2017) and work (Howard et al., 2016) domain showed a shift in magnitude and sign along the continuum from intrinsic motivation to amotivation. Both these studies found decreases in the magnitude of factor loadings from intrinsic motivation to external regulation, whereas a shift in sign from positive to negative loadings was observed between external regulation and amotivation. There were, however, some inconsistencies regarding the magnitude of the factor loadings that are worth mentioning. In Howard et al. (2016), there was not a clear distinction in magnitude of the factor loadings between intrinsic motivation ($M\lambda$ = .73) and identified regulation ($M\lambda$ = .69). In Litalien et al. (2017) there was not a clear distinction in the magnitude of the factor loadings between identified (Study 1 $M\lambda$ = .46, Study 2 $M\lambda$ = .33) and introjected regulation (Study 1 $M\lambda$ = .52, Study 2 $M\lambda$ = .37). A third bifactor ESEM study, in a physical activity context, showed a slightly different pattern of factor loadings onto the general factor where all items (including the amotivation items) had moderate and positive loadings (Gunnell & Gaudreau, 2015). These previous findings combined with the results from the present study do to some extent support a continuum structure using measures of academic (Academic Motivation Scale [AMS]; Litalien et al., 2017), exercise (Behavioral Regulation in Exercise Questionnaire-2 [BREQ-2]; Gunnell & Gaudreau, 2015), sport (BRSQ; the present study), and work (Multidimensional Work Motivation Scale [MWMS]; Howard et al., 2016) motivation, but they also show inconsistencies between these studies that needs further investigation. Although a recent meta-analysis showed that the continuum structure appears to be relatively stable across domain, scale used, nationality, age, and gender, heterogeneity remained that was not explained by these moderators (Howard, Gagné, & Bureau, 2017). Researchers have suggested that the associations between the regulations may be inherently heterogeneous (Chatzisarantis, Hagger, Biddle, Smith, & Wang, 2003), however, that does not rule out the possibility that other moderators (e.g., contextual factors) may be causing (at least some) of the heterogeneity (Howard et al., 2017).

Limitations and Suggestions for Future Research

Some limitations are noticeable in the present study. First, the sample was restricted to young athletes in Sweden representing a narrow range of sports (floorball and skiing). Whether these results replicate to other settings, such as older or younger athletes, other sports, levels, and cultures should be examined in future research. As highlighted in previous research (e.g., Chemolli & Gagné, 2014; Howard et al., 2016), there appear to be more variability in the pattern of correlations between the motivation subscales across studies than what is outlined in SDT, and the results from the present study further adds to that variability. The causes of this variability are important to tease out in future research, by examining potential moderating factors within and across domains. Second, we did not address the potential causes of the latent mean changes in the behavioral regulations across the season. Using various data sources, preferably objective data on individual and team performance, injuries, and data on other influential sources such as coach, peer, and parental behaviors could potentially increase our understanding of changes in motivation across the athletic season. Third, we were unable to examine longitudinal measurement invariance in the bifactor ESEM model due to estimation problems and inadmissible solutions. Whether the *quantity* of motivation, as defined by the global factor in the bifactor ESEM model, changes across the athletic season (or across some other meaningful time span) would be interesting to explore in future research.

Finally, the negative error variance of the identified regulation item 9 ("*because the benefits of sport are important to me*") in the bifactor ESEM at T2 warrants further attention. Researchers have proposed several potential causes of "Heywood cases" or negative variance estimates in factor analysis and structural equation modeling, such as nonconvergence, outliers, underidentification, empirical underidentification, structural misspecification, or sampling fluctuations (e.g., Chen, Bollen, Paxton, Curran, & Kirby, 2001; Kolenikov & Bollen, 2012). Different remedies have been proposed to deal with Heywood cases. For example, when certain conditions are met, such as when the negative variance estimate is small, not statistically significant, and its confidence interval (CI) encompasses zero, it can be constrained to zero or a small positive value (Chen et al., 2001; Kolenikov & Bollen, 2012). Although the negative error variance estimate was not statistically significant and its CI encompassed zero, the error variance estimate (δ = -1.093) and the standardized factor loading on the specific factor (λ = 1.336) was large. We constrained the negative residual variance to zero or a small positive value but the estimation problem persisted despite these constraints. It may be that the general factor did not account for unique variance in the indicator when the domain-specific factor was partialed out; that is, the negative residual variance estimate may be a consequence of empirical underidentification due to weak factor loadings (Brown, 2015).

Conclusions

The present study contributes to the ongoing psychometric evaluation of the BRSQ and adds longitudinal measurement invariance as another piece of evidence for this tool. These results are reassuring as they suggest that researchers can use the BRSQ to address complex questions about changes in the behavioral regulations over time, for example in interventions studies. Furthermore, we observed changes in the latent means of the behavioral regulations (i.e., increases in external regulation and amotivation) across the athletic season, which previously have been found in other domains, (e.g., education, Gnamb & Hanfstingl, 2016), but not in the sports domain. An important avenue for future research is to understand why these changes occur by including important predictors (cf. Gnamb & Hanfstingl, 2016) as well as the consequences of these changes (cf. Otis et al., 2005). Such research could potentially prevent or minimize the negative effects of increased external regulation and amotivation as well as find ways to optimize young athletes' motivation throughout an athletic season.

As previously demonstrated in the educational (Litalien et al., 2017), physical activity (Gunnell & Gaudreau, 2015), and work (Howard et al., 2016) domains, the present study also highlights the usefulness of the bifactor ESEM framework to test SDTs continuum hypothesis in the sports domain. The bifactor ESEM framework allows for a more rigorous test of the continuum hypothesis compared to many other techniques, such as ICM-CFA (e.g., Hancox et al., 2015; Lonsdale et al., 2008) or Rasch modeling (e.g., Chemolli & Gagne, 2014). With a bifactor ESEM model, we can simultaneously take into account motivation *quantity* (i.e., the global factor) and motivation *quality* (i.e., the specific motivation factors). Many researchers have used the relative autonomy index (RAI), which is calculated by weighting the behavioral regulations according to their placement of the continuum resulting in a single construct representing quantity of self-determined motivation. The RAI is a difference score, which encompasses problems that are well documented in the literature (e.g., Edwards, 2001), and the commonly applied weighting formula (i.e., the "distance between the regulations) have been criticized for its lack of validity evidence (Chemolli & Gagne, 2014). In addition, previous research has shown that a single construct representing quantity of self-determined motivation is insufficient to explain motivational covariates (Howard et al., 2016). The orthogonality of the bifactor ESEM model allows for simultaneously test how motivation *quantity* and *quality* are associated with covariates without the risk of multicollinearity between the motivation subscales, which is one of the key advantages of the bifactor model. Finally, the present research provide evidence of the psychometric properties of the Swedish version of the BRSQ, thus contributing to the ability to conduct cross-cultural studies.

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Figure Caption

Figure 1. ESEM (left) and bifactor ESEM (right) of the behavioral regulations. The dashed lines indicate non-target factor loadings.

Table 1

Means, Standard Deviations, Skewness, and Kurtosis of all Items at T1 and T2

	T1				T2			
	M	*SD*	Skewness	Kurtosis	*M*	*SD*	Skewness	Kurtosis
IM1	6.72	0.66	-2.99	10.48	6.68	0.68	-2.70	8.52
IM11	6.69	0.82	-3.73	17.13	6.58	0.89	-2.72	8.70
IM15	6.68	0.73	-2.61	7.10	6.60	0.85	-2.47	6.13
IM18	6.50	0.95	-2.65	8.49	6.46	0.90	-1.75	2.46
ID9	4.72	1.82	-0.48	-0.66	4.82	1.86	-0.57	-0.62
ID16	4.49	1.74	-0.31	-0.72	4.53	1.82	-0.37	-0.73
ID20	5.63	1.57	-1.18	0.71	5.53	1.64	-1.15	0.69
ID22	4.85	1.82	-0.51	-0.68	4.94	1.78	-0.58	-0.43
IJ4	1.79	1.41	2.10	3.92	2.09	1.62	1.48	1.31
IJ6	1.96	1.52	1.76	2.30	1.95	1.46	1.69	2.24
IJ12	1.73	1.34	2.20	4.59	1.99	1.52	1.59	1.73
IJ17	1.93	1.53	1.72	2.01	1.97	1.50	1.65	1.91
EX10	1.80	1.38	1.99	3.28	1.97	1.41	1.52	1.63
EX14	1.46	0.98	2.76	8.69	1.72	1.28	2.06	3.74
EX19	1.46	1.04	2.97	9.54	1.68	1.30	2.34	5.14
EX23	1.60	1.22	2.40	5.42	1.83	1.46	1.97	3.18
AM5	1.56	1.15	2.38	5.29	1.80	1.39	1.94	3.10
AM7	1.58	1.20	2.49	5.95	1.74	1.30	2.00	3.54
AM13	1.64	1.20	2.28	5.18	1.82	1.41	1.92	3.12
AM21	1.74	1.33	2.03	3.73	1.78	1.32	1.93	3.41

Note. IM = intrinsic motivation, ID = identified regulation, IJ = introjected regulation, EX = external regulation, AM = amotivation.

Table 2

Longitudinal Measurement Invariance and Bifactor ESEM of the Swedish Version of the Five-Factor BRSQ. ESEM With Target Rotation was Used in all Analyses Except the ICM-CFA (N = 354)

Model	$\chi 2$	*df*	*p*	RMSEA [90%CI)	CFI	TLI	SRMR
ICM-CFA							
T1	260.060	160	0.000	0.042 [0.033, 0.051]	0.948	0.939	0.048
T2	337.408	160	0.000	0.056 [0.048, 0.064]	0.919	0.904	0.054
ESEM							
T1	169.799	100	0.000	0.044 [0.033, 0.056]	0.964	0.931	0.021
T2	174.685	100	0.000	0.046 [0.034, 0.057]	0.966	0.935	0.022
Configural	854.424	555	0.000	0.039 [0.034, 0.044]	0.946	0.924	0.031
Metric	960.830	630	0.000	0.039 [0.034, 0.043]	0.940	0.926	0.043
Scalar	1006.231	650	0.000	0.039 [0.035, 0.044]	0.936	0.923	0.046
Strict	1004.389	670	0.000	0.038 [0.033, 0.042]	0.940	0.930	0.052
Latent Means	992.742	665	0.000	0.037 [0.032, 0.042]	0.941	0.931	0.051
Bifactor T1	146.299	85	0.000	0.045 [0.032, 0.057]	0.968	0.929	0.019
Bifactor T2[a]	96.613	72	0.028	0.031 [0.011, 0.046]	0.988	0.970	0.015

[a]Identified regulation item 9 excluded due to negative error variance ("*because the benefits of sport are important to me*").

Table 3

Standardized ESEM Factor Loadings and Uniquenesses From the Most Invariant Longitudinal ESEM Model

	T1						T2					
	IM (λ)	ID (λ)	IJ (λ)	EX (λ)	AM (λ)	δ	IM (λ)	ID (λ)	IJ (λ)	EX (λ)	AM (λ)	δ
IM1	**0.707**	0.039	-0.060	0.053	-0.046	0.448	**0.740**	0.038	-0.063	0.065	-0.054	0.396
IM11	**0.731**	-0.039	0.070	-0.088	-0.078	0.371	**0.752**	-0.038	0.072	-0.107	-0.090	0.317
IM15	**0.875**	-0.027	0.019	-0.044	-0.033	0.181	**0.887**	-0.026	0.019	-0.053	-0.038	0.149
IM18	**0.624**	0.101	0.047	-0.010	-0.145	0.454	**0.651**	0.100	0.049	-0.012	-0.169	0.398
ID9	-0.048	**0.679**	0.056	0.007	-0.062	0.541	-0.052	**0.691**	0.059	0.008	-0.075	0.504
ID16	-0.057	**0.609**	0.128	-0.036	-0.047	0.615	-0.062	**0.622**	0.137	-0.046	-0.058	0.577
ID20	0.105	**0.667**	-0.083	0.011	0.051	0.526	0.115	**0.691**	-0.091	0.014	0.063	0.508
ID22	0.024	**0.773**	-0.077	0.006	0.055	0.407	0.026	**0.796**	-0.083	0.007	0.067	0.389
IJ4	0.008	0.075	**0.687**	-0.065	0.079	0.508	0.008	0.075	**0.720**	-0.081	0.094	0.457
IJ6	0.067	0.034	**0.429**	0.139	0.236	0.508	0.070	0.033	**0.442**	0.171	0.275	0.442
IJ12	-0.037	-0.019	**0.735**	0.000	0.035	0.411	-0.039	-0.018	**0.763**	0.000	0.041	0.363
IJ17	-0.027	-0.022	**0.646**	0.210	-0.075	0.378	-0.029	-0.022	**0.670**	0.259	-0.089	0.333
EX10	-0.028	-0.017	0.294	**0.520**	-0.032	0.403	-0.028	-0.016	0.291	**0.614**	-0.036	0.325
EX14	-0.077	-0.007	0.123	**0.591**	0.094	0.366	-0.073	-0.007	0.116	**0.666**	0.100	0.268
EX19	0.024	-0.065	-0.045	**0.684**	0.109	0.512	0.023	-0.058	-0.041	**0.755**	0.114	0.361
EX23	-0.046	0.061	-0.071	**0.749**	-0.015	0.494	-0.043	0.054	-0.066	**0.834**	-0.016	0.355
AM5	-0.101	-0.030	0.105	-0.120	**0.716**	0.391	-0.100	-0.028	0.104	-0.141	**0.797**	0.310
AM7	0.015	-0.086	0.120	-0.007	**0.659**	0.475	0.014	-0.080	0.117	-0.008	**0.729**	0.371
AM13	-0.126	0.049	-0.051	0.131	**0.631**	0.406	-0.121	0.044	-0.049	0.149	**0.681**	0.302
AM21	-0.011	0.090	0.057	0.145	**0.469**	0.603	-0.011	0.086	0.057	0.173	**0.533**	0.498

Note. Target factor loadings are highlighted in bold. IM = intrinsic motivation, ID = identified regulation, IJ = introjected regulation, EX = external regulation, AM = amotivation, λ = factor loadings, δ = uniquenesses

Table 4

Latent Factor Correlations from the Strict Invariance Model and Internal Consistency (ω)

	T1IM	T1ID	T1IJ	T1EX	T1AM	T2IM	T2ID	T2IJ	T2EX	T2AM
T1IM	0.80									
T1ID	0.23***	0.72								
T1IJ	-0.32***	0.19***	0.74							
T1EX	-0.44***	0.11	0.84***	0.74						
T1AM	-0.64***	0.07	0.63***	0.58***	0.73					
T2IM	0.63***	0.15*	-0.26***	-0.37***	-0.43***	0.83				
T2ID	0.10	0.55***	0.13*	0.06	-0.01	0.19**	0.74			
T2IJ	-0.27***	0.14*	0.62***	0.50***	0.38***	-0.34***	0.21***	0.77		
T2EX	-0.29***	-0.07	0.41***	0.60***	0.29**	-0.40***	0.07	0.66***	0.81	
T2AM	-0.38***	-0.06	0.43***	0.41***	0.47***	-0.59***	-0.08	0.55***	0.68***	0.79

Note. IM = intrinsic motivation, ID = identified regulation, IJ = introjected regulation, EX = external regulation, AM = amotivation,

**p* < .05, ***p* < .01, ****p* < .001.

Omega coefficients (ω) are displayed in the diagonal.

Table 5

Bifactor ESEM Factor Loadings and Uniquenesses

	T1							T2[a]						
	G (λ)	IM (λ)	ID (λ)	IJ (λ)	EX (λ)	AM (λ)	δ	G (λ)	IM (λ)	ID (λ)	IJ (λ)	EX (λ)	AM (λ)	δ
IM1	-0.454	**0.633**	0.118	-0.016	0.016	-0.153	0.356	-0.432	**0.591**	0.101	-0.014	0.040	0.008	0.452
IM11	-0.618	**0.573**	0.043	0.206	0.309	0.116	0.136	-0.520	**0.667**	0.047	0.029	-0.041	-0.108	0.268
IM15	-0.547	**0.703**	0.139	0.052	-0.064	-0.140	0.161	-0.550	**0.686**	0.054	0.036	0.033	-0.072	0.217
IM18	-0.352	**0.642**	0.134	-0.029	-0.183	-0.156	0.387	-0.502	**0.573**	0.185	0.074	0.061	-0.122	0.360
ID9	-0.005	0.039	**0.679**	0.126	0.161	-0.030	0.495							
ID16	0.180	0.138	**0.559**	0.026	-0.065	-0.016	0.632	0.062	0.039	**0.631**	0.130	-0.031	-0.076	0.572
ID20	-0.009	0.147	**0.701**	0.037	-0.060	-0.040	0.480	-0.065	0.205	**0.490**	0.011	0.067	0.021	0.709
ID22	0.048	0.105	**0.733**	-0.003	-0.024	0.068	0.444	-0.022	0.118	**0.930**	0.050	0.014	0.004	0.118
IJ4	0.514	0.056	0.101	**0.520**	-0.007	-0.004	0.452	0.572	0.060	0.147	**0.505**	-0.020	0.037	0.391
IJ6	0.547	0.091	0.124	**0.534**	-0.021	0.087	0.383	0.842	0.093	0.024	**0.004**	-0.082	-0.051	0.273
IJ12	0.778	0.105	0.016	**0.082**	0.089	-0.057	0.365	0.598	0.067	0.056	**0.560**	-0.064	0.028	0.316
IJ17	0.718	0.143	0.015	**0.279**	0.132	-0.044	0.366	0.655	0.024	0.066	**0.436**	0.197	-0.058	0.334
EX10	0.712	0.048	0.029	0.096	**0.324**	-0.102	0.365	0.788	0.119	0.003	0.101	**0.135**	-0.083	0.329
EX14	0.778	0.082	-0.001	0.079	**0.274**	0.039	0.305	0.851	-0.009	0.021	-0.077	**0.151**	-0.107	0.236
EX19	0.647	-0.030	-0.053	-0.054	**0.344**	-0.019	0.456	0.645	0.041	-0.010	0.084	**0.529**	0.114	0.283
EX23	0.610	-0.008	0.065	-0.014	**0.337**	-0.075	0.504	0.692	0.054	0.086	-0.022	**0.322**	-0.031	0.405
AM5	0.620	-0.193	-0.046	0.012	-0.090	**0.581**	0.231	0.627	-0.206	-0.049	0.071	-0.076	**0.429**	0.367
AM7	0.614	-0.106	-0.058	0.050	-0.076	**0.377**	0.457	0.669	-0.082	-0.108	0.018	-0.046	**0.352**	0.407
AM13	0.645	-0.144	0.070	-0.009	0.045	**0.345**	0.437	0.723	-0.182	0.000	-0.120	0.038	**0.417**	0.255
AM21	0.532	-0.165	0.102	0.032	0.068	**0.166**	0.646	0.644	0.017	0.063	0.056	0.142	**0.392**	0.403

Note. Target factor loadings are highlighted in bold. G = general factor, IM = intrinsic motivation, ID = identified regulation, IJ = introjected regulation, EX = external regulation, AM = amotivation, λ = factor loadings, δ = uniquenesses. [a]Identified regulation item 9 ("*because the benefits of sport are important to me*") was excluded due to negative error variance.

SUPPLEMENTARY MATERIALS APPENDIX 1.1

MPLUS SYNTAX FOR THE CONFIGURAL INVARIANCE MODEL

```
TITLE: Longitudinal measurement invariance

DATA:
FILE IS "C:\Users\anslil01\Documents\Longitudinal approximate MI (BRSQ, BNSSS)\Long
MI BRSQ.dat";

VARIABLE:
NAMES ARE
ORGFpNr Dataset T1Sex T1Age T1Sport
T1StAge YiSp T1Level T1PrHw T1YwC
T1INJ
T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_IG2 T1_IG3 T1_IG8 T1_IG24
T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_AM5 T1_AM7 T1_AM13 T1_AM21
T2INJ
T2_IM1 T2_IM11 T2_IM15 T2_IM18
T2_IG2 T2_IG3 T2_IG8 T2_IG24
T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IJ4 T2_IJ12 T2_IJ6 T2_IJ17
T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_AM5 T2_AM7 T2_AM13 T2_AM21;

USEVARIABLES ARE
!T1
T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_AM5 T1_AM7 T1_AM13 T1_AM21
!T2
T2_IM1 T2_IM11 T2_IM15 T2_IM18
T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IJ4 T2_IJ6 T2_IJ12 T2_IJ17
T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_AM5 T2_AM7 T2_AM13 T2_AM21;

MISSING ARE ALL (-999);

ANALYSIS:
ESTIMATOR IS MLR; !maximum likelihood parameter estimates with standard errors and a
chi-square test statistic (when applicable) that are robust to non-normality. The MLR standard
errors are computed using a sandwich estimator.
ROTATION = TARGET; !specifies target rotation (default is oblique target rotation).
```

OUTPUT: SAMPSTAT STDYX TECH1 TECH4 CINTERVAL MODINDICES(ALL);

MODEL:
!MODEL T1
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are "targeted" to be close to zero. The (*1) indicates that IM1, ID1, IJ1, EX1, and AM1 are a set of EFA factors.
IM1 BY T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

ID1 BY T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

IJ1 BY T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

EX1 BY T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

AM1 BY T1_AM5 T1_AM7 T1_AM13 T1_AM21
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0(*1);

!MODEL T2
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are "targeted" to be close to zero. The (*2) indicates that IM2, ID2, IJ2, EX2, and AM2 are a set of EFA factors.
IM2 BY T2_IM1 T2_IM11 T2_IM15 T2_IM18
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2);

ID2 BY T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0

```
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2);

IJ2 BY T2_IJ4 T2_IJ6 T2_IJ12 T2_IJ17
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2);

EX2 BY T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2);

AM2 BY T2_AM5 T2_AM7 T2_AM13 T2_AM21
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0(*2);

!correlate the item’s uniqueness across time
T1_IM1-T1_AM21 PWITH T2_IM1-T2_AM21;
```

SUPPLEMENTARY MATERIALS APPENDIX 1.2

MPLUS SYNTAX FOR THE METRIC INVARIANCE MODEL

MODEL:
!MODEL T1
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are "targeted" to be close to zero. The (*1) indicates that IM1, ID1, IJ1, EX1, and AM1 are a set of EFA factors. The second digit in the parentheses places equality constraints on the factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and IM2.

```
IM1 BY T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 1);

ID1 BY T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 2);

IJ1 BY T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 3);

EX1 BY T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 4);

AM1 BY T1_AM5 T1_AM7 T1_AM13 T1_AM21
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0(*1 5);
```

!MODEL T2
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are "targeted" to be close to zero. The (*2) indicates that IM2, ID2, IJ2, EX2, and AM2 are a set of EFA factors. The second digit in the parentheses places equality constraints on the factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and IM2.

```
IM2 BY T2_IM1 T2_IM11 T2_IM15 T2_IM18
```

```
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 1);

ID2 BY T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 2);

IJ2 BY T2_IJ4 T2_IJ6 T2_IJ12 T2_IJ17
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 3);

EX2 BY T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 4);

AM2 BY T2_AM5 T2_AM7 T2_AM13 T2_AM21
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0(*2 5);

!correlate the item’s uniqueness across time
T1_IM1-T1_AM21 PWITH T2_IM1-T2_AM21;
```

SUPPLEMENTARY MATERIALS APPENDIX 1.3

MPLUS SYNTAX FOR THE SCALAR INVARIANCE MODEL

```
MODEL:
!MODEL T1
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings
that are “targeted” to be close to zero. The (*1) indicates that IM1, ID1, IJ1, EX1, and AM1
are a set of EFA factors. The second digit in the parentheses places equality constraints on the
factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and
IM2.

IM1 BY T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 1);

ID1 BY T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 2);

IJ1 BY T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 3);

EX1 BY T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 4);

AM1 BY T1_AM5 T1_AM7 T1_AM13 T1_AM21
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0(*1 5);

!MODEL T2
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings
that are “targeted” to be close to zero. The (*2) indicates that IM2, ID2, IJ2, EX2, and AM2
are a set of EFA factors. The second digit in the parentheses places equality constraints on the
factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and
IM2.

IM2 BY T2_IM1 T2_IM11 T2_IM15 T2_IM18
```

```
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 1);

ID2 BY T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 2);

IJ2 BY T2_IJ4 T2_IJ6 T2_IJ12 T2_IJ17
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 3);

EX2 BY T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 4);

AM2 BY T2_AM5 T2_AM7 T2_AM13 T2_AM21
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0(*2 5);

!correlate the item’s uniqueness across time
T1_IM1-T1_AM21 PWITH T2_IM1-T2_AM21;

!equality constrains on the intercepts
[T1_IM1-T1_AM21](I1-I20);
[T2_IM1-T2_AM21](I1-I20);
```

SUPPLEMENTARY MATERIALS APPENDIX 1.4

MPLUS SYNTAX FOR THE STRICT INVARIANCE MODEL

MODEL:
!MODEL T1
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are “targeted” to be close to zero. The (*1) indicates that IM1, ID1, IJ1, EX1, and AM1 are a set of EFA factors. The second digit in the parentheses places equality constraints on the factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and IM2.

IM1 BY T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 1);

ID1 BY T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 2);

IJ1 BY T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 3);

EX1 BY T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 4);

AM1 BY T1_AM5 T1_AM7 T1_AM13 T1_AM21
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0(*1 5);

!MODEL T2
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are “targeted” to be close to zero. The (*2) indicates that IM2, ID2, IJ2, EX2, and AM2 are a set of EFA factors. The second digit in the parentheses places equality constraints on the factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and IM2.

IM2 BY T2_IM1 T2_IM11 T2_IM15 T2_IM18

```
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 1);

ID2 BY T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 2);

IJ2 BY T2_IJ4 T2_IJ6 T2_IJ12 T2_IJ17
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 3);

EX2 BY T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 4);

AM2 BY T2_AM5 T2_AM7 T2_AM13 T2_AM21
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0(*2 5);

!correlate the item’s uniqueness across time
T1_IM1-T1_AM21 PWITH T2_IM1-T2_AM21;

!equality constrains on the intercepts
[T1_IM1-T1_AM21](I1-I20);
[T2_IM1-T2_AM21](I1-I20);

!equality constrains on the item’s uniqueness
T1_IM1-T1_AM21(rv1-rv20);
T2_IM1-T2_AM21(rv1-rv20);
```

SUPPLEMENTARY MATERIALS APPENDIX 1.5

MPLUS SYNTAX FOR THE STRICT INVARIANCE MODEL FREELY ESTIMATING THE LATENT MEANS AT T2

MODEL:
!MODEL T1
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are “targeted” to be close to zero. The (*1) indicates that IM1, ID1, IJ1, EX1, and AM1 are a set of EFA factors. The second digit in the parentheses places equality constraints on the factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and IM2.

IM1 BY T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 1);

ID1 BY T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 2);

IJ1 BY T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 3);

EX1 BY T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1 4);

AM1 BY T1_AM5 T1_AM7 T1_AM13 T1_AM21
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0(*1 5);

!MODEL T2
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are “targeted” to be close to zero. The (*2) indicates that IM2, ID2, IJ2, EX2, and AM2 are a set of EFA factors. The second digit in the parentheses places equality constraints on the factor loadings. For example, the (*1 1) and (*2 1) specifies equal factor loadings for IM1 and IM2.

```
IM2 BY T2_IM1 T2_IM11 T2_IM15 T2_IM18
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 1);

ID2 BY T2_ID9 T2_ID16 T2_ID20 T2_ID22
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 2);

IJ2 BY T2_IJ4 T2_IJ6 T2_IJ12 T2_IJ17
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 3);

EX2 BY T2_EX10 T2_EX14 T2_EX19 T2_EX23
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_AM5~0 T2_AM7~0 T2_AM13~0 T2_AM21~0(*2 4);

AM2 BY T2_AM5 T2_AM7 T2_AM13 T2_AM21
T2_IM1~0 T2_IM11~0 T2_IM15~0 T2_IM18~0
T2_ID9~0 T2_ID16~0 T2_ID20~0 T2_ID22~0
T2_IJ4~0 T2_IJ6~0 T2_IJ12~0 T2_IJ17~0
T2_EX10~0 T2_EX14~0 T2_EX19~0 T2_EX23~0(*2 5);

!correlate the item's uniqueness across time
T1_IM1-T1_AM21 PWITH T2_IM1-T2_AM21;

!equality constrains on the intercepts
[T1_IM1-T1_AM21](I1-I20);
[T2_IM1-T2_AM21](I1-I20);

!equality constrains on the item's uniqueness
T1_IM1-T1_AM21(rv1-rv20);
T2_IM1-T2_AM21(rv1-rv20);

!latent means set to zero at T1 and freely estimated at T2
[IM1-AM1@0];
[IM2-AM2];
```

SUPPLEMENTARY MATERIALS APPENDIX 1.6

MPLUS SYNTAX FOR THE BIFACTOR EXPLORATORY STRUCTURAL EQUATION MODEL

ANALYSIS:
ESTIMATOR IS MLR; !maximum likelihood parameter estimates with standard errors and a chi-square test statistic (when applicable) that are robust to non-normality. The MLR standard errors are computed using a sandwich estimator.
ROTATION = TARGET(ORTHOGONAL); !specifies target rotation. Specifying orthogonal in the parenthesis overrides the default oblique rotation.

MODEL:
!Freely estimated main loadings. The ~0 after the non-target loadings specifies cross-loadings that are “targeted” to be close to zero. The (*1) indicates that IM1, ID1, IJ1, EX1, AM1, and G1 are a set of EFA factors.
IM1 BY T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

ID1 BY T1_ID9 T1_ID16 T1_ID20 T1_ID22
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

IJ1 BY T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

EX1 BY T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_AM5~0 T1_AM7~0 T1_AM13~0 T1_AM21~0(*1);

AM1 BY T1_AM5 T1_AM7 T1_AM13 T1_AM21
T1_IM1~0 T1_IM11~0 T1_IM15~0 T1_IM18~0
T1_ID9~0 T1_ID16~0 T1_ID20~0 T1_ID22~0
T1_IJ4~0 T1_IJ6~0 T1_IJ12~0 T1_IJ17~0
T1_EX10~0 T1_EX14~0 T1_EX19~0 T1_EX23~0(*1);

G1 by
T1_IM1 T1_IM11 T1_IM15 T1_IM18
T1_ID9 T1_ID16 T1_ID20 T1_ID22

T1_IJ4 T1_IJ6 T1_IJ12 T1_IJ17
T1_EX10 T1_EX14 T1_EX19 T1_EX23
T1_AM5 T1_AM7 T1_AM13 T1_AM21(*1);

SUPPLEMENTARY MATERIALS APPENDIX 2.0

CROSS-CULTURAL EQUIVALENCE OF THE BRSQ

To further test the psychometric properties of the Swedish version of the BRSQ we examined cross-cultural equivalence by means of measurement invariance testing. We included data collected from New Zealand-based athletes (*N* = 529) reported in a previously published paper (Lonsdale et al., 2008) who responded to the original English version of the BRSQ. We collapsed the samples from Study 1, 2, and 3 reported in Lonsdale et al. (2008) and only included athletes in the same age range as the Swedish sample (i.e., 15-21 years). The mean age of the New Zealand sample was 18.9 (*SD* = 1.39) and comprised 230 males (43.6%) and 297 females (56.4%); 2 athletes did not report sex. A more detailed description of the different sports and competitive levels covered in the sample is provided in Lonsdale et al. (2008). The New Zealand sample was compared to the Swedish sample at T1 to examine cross-cultural equivalence of the BRSQ using ESEM.

We specified increasingly constrained models to examine measurement invariance in the BRSQ following the Meredith (1993) tradition. First, a configural model is estimated, which evaluates the similarity in the overall pattern of parameters between the two groups. No equality constraints are imposed in the configural model; it provides a test of the a priori model in each group and how it fits the data against which subsequent models with constraints can be compared. Second, a metric invariance model is estimated in which the factor loadings are constrained to be invariant across groups. Third, a scalar invariance model is estimated where the item intercepts and factor loadings are constrained to be invariant across groups. Model fit was evaluated with conventional fit indices such as the comparative fit index (CFI), the Tucker-Lewis Index (TLI), the standardized root mean residual (SRMR), and the root mean square error of approximation (RMSEA). CFI and TLI values around 0.90 and SRMR and RMSEA values around 0.08 indicated acceptable model fit (Marsh, 2007). The nested invariance models were evaluated using Chen's (2007) recommendations that change in CFI (ΔCFI) of less than 0.01 and change in RMSEA (ΔRMSEA) of less than 0.015 or a change in SRMR (ΔSRMR) of less than 0.030 would support metric invariance. For scalar invariance a change in CFI (ΔCFI) of less than 0.01 and change in RMSEA (ΔRMSEA) of less than 0.015 or a change in SRMR (ΔSRMR) of less than 0.010 would indicate invariance across groups.

As seen in Table S1, configural and metric invariance were supported, whereas scalar invariance was not according to the decrease in CFI (ΔCFI = 0.019). Hence, we inspected the modification indices (MI) for non-invariant intercepts. The MI provides an approximation of how much the overall $\chi 2$ will decrease if a fixed or constrained parameter is estimated freely (Brown & Moore, 2012). The MI can be conceptualized as a $\chi 2$ statistic with 1 df; as such, a critical value of 3.84 is statistically significant at $p < 0.05$. We inspected constrained intercepts with MI values larger than 10 (the default in Mplus) because these are more likely to reflect changes that will substantially improve the model fit. Three potentially non-invariant intercepts were identified regulation item 9 ("*because the benefits of sport are important to me*"), identified regulation item 22 ("*because it is a good way to learn things which could be useful to me in my life*"), and external regulation item 10 ("*because if I don't other people will not be pleased with me*")–with MI values ranging from 20.08 to 42.67. Freely estimating these intercepts did result in a model that supported partial scalar invariance in the BRSQ. A closer look at the intercept values show that the New Zealand athletes scored higher on identified regulation item 9 (6.13 vs 5.42) and lower on identified regulation item 22 (5.06 vs 5.63) and external regulation item 10 (2.43 vs. 2.84) compared to the Swedish athletes. These results tentatively suggest that the meaning of these items may differ between athletes in these two cultures.

Table S1

Cross-cultural Equivalence of the BRSQ Based on ESEM Models

Model	$\chi2$	*df*	*p*	RMSEA [90%CI)	CFI	TLI	SRMR
New Zealand sample	276.657	100	0.000	0.058 [0.050, 0.066]	0.967	0.937	0.022
Swedish sample	169.799	100	0.000	0.044 [0.033, 0.056]	0.964	0.931	0.021
Configural	450.572	200	0.000	0.053 [0.047, 0.060]	0.964	0.931	0.022
Metric	540.810	275	0.000	0.047 [0.041, 0.053]	0.962	0.947	0.050
Scalar	683.365	290	0.000	0.055 [0.050, 0.061]	0.943	0.925	0.055
Partial scalar[a]	600.939	287	0.000	0.050 [0.044, 0.055]	0.955	0.940	0.052

Note. [a]Intercepts of identified regulation item 9 ("*because the benefits of sport are important to me*"), 22 ("*because it is a good way to learn things which could be useful to me in my life*"), and external regulation item 10 ("*because if I don't other people will not be pleased with me*"), were freely estimated.

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